A synergy-driven approach to a myoelectric hand

S.B. Godfrey, A. Ajoudani, M. Catalano, G. Grioli, A. Bicchi

Abstract— **In this paper, we present the Pisa/IIT SoftHand with myoelectric control as a synergy-driven approach for a prosthetic hand. Commercially available myoelectric hands are more expensive, heavier, and less robust than their body-powered counterparts; however, they can offer greater freedom of motion and a more aesthetically pleasing appearance. The Pisa/IIT SoftHand is built on the motor control principle of synergies through which the immense complexity of the hand is simplified into distinct motor patterns. As the SoftHand grasps, it follows a synergistic path with built-in flexibility to allow grasping of a wide variety of objects with a single motor. Here we test, as a proof-of-concept, 4 myoelectric controllers: a standard controller in which the EMG signal is used only as a position reference, an impedance controller that determines both position and stiffness references from the EMG input, a standard controller with vibrotactile force feedback, and finally a combined vibrotactile-impedance (VI) controller. Four healthy subjects tested the control algorithms by grasping various objects. All controllers were sufficient for basic grasping, however the impedance and vibrotactile controllers reduced the physical and cognitive load on the user, while the combined VI mode was the easiest to use of the four. While these results need to be validated with amputees, they suggest a low-cost, robust hand employing hardware-based synergies is a viable alternative to traditional myoelectric prostheses.**

I. INTRODUCTION

Approximately one person out of every 200 in the United States has lost a limb [1]. Global statistics are difficult to estimate, but the causes are predominately war, disease, and trauma, biased toward the former in under-developed countries and the latter two in the developed world [2]. There is typically great functional and psychological loss following amputation. As a result, prostheses have emerged to cover a variety of functions, from cosmetic to restore appearance, to lightweight body-powered hooks to provide basic functionality with limited cost and weight (eg: from Hosmer, Fillauer LLC), to single or multi-degree of freedom, anthropomorphic hands controlled by muscle signals (myoelectric hands, eg: the DMC Plus®hand from Otto Bock or the i-limb™ultra from Touch Bionics, Inc).

Currently, both body-powered and myoelectric prostheses are commonly used. The former offer a lightweight design that is typically more able to withstand vigorous use and harsh environments. The latter, while often more costly and heavier than the body-powered alternative, are more aesthetically pleasing and can provide the user with greater control over the functioning of the hand [3]. Despite the increased function of the newest hands, the cognitive load and muscle control required prevents some amputees from adopting the latest technology or using it to the fullest [3]. Much research is now focused on shifting the cognitive burden to the control architecture of the hand rather than the user: by using machine learning techniques, EMG signals harvested from multi-channel systems determine user intent and translate that to the hand, eg in [4], [5]. These systems, however, often require large numbers of electrodes, the placement of which ranges from merely tedious to impossible depending on the length of the stump. Also, complex machine learning algorithms require large training sets to be properly calibrated. The complexity of the innate control and sensing of the human hand is extremely difficult to replicate. For example, humans continuously vary the stiffness and force of their muscles to adapt to the requirements of their situation. In order to modulate these features effectively, humans rely heavily on the tactile sensors of the hand. To enhance functionality of prostheses, features such as impedance control [6], [7] and vibrotactile feedback [8] are being explored in research settings.

In this article, we introduce myoelectric control of the Pisa/IIT SoftHand [9]. The SoftHand is built on the principle of synergies: through synergies, the brain is able to simplify the control of the many degree of freedom hand [10]. By including synergies in the mechanical design of the SoftHand, the requisite control architecture is greatly simplified without compromising the function of the device. For myoelectric control, we harvest EMG signals from two electrodes placed on the proximal forearm, thus minimizing set up time and improving the likelihood the user will have sufficient muscle to control the device. From these two signals, we determine desired position as well as impedance. The impedance control is a simplified version of that used in this lab previously to modulate a robotic arm [11]. In order to improve control of the device and minimize the user's reliance on visual feedback, vibrotactile feedback proportional to force was included. The impedance and vibrotactile feedback features are evaluated against a simple position controller for ease of use and physical and cognitive load. The SoftHand, with its built-in synergies, eliminates the need to choose a grasp pattern, thus reducing the cognitive burden on the user while achieving functional results. A video demonstrating the SoftHand grasping various objects and illustrating impedance control can be found at [12]. Body-powered hands provide a robust design at low cost whereas myoelectrics offer greater function but with increased cognitive load. It is the goal of this study to provide proof-of-concept for a low cost, low cognitive load hand capable of grasping a variety of objects

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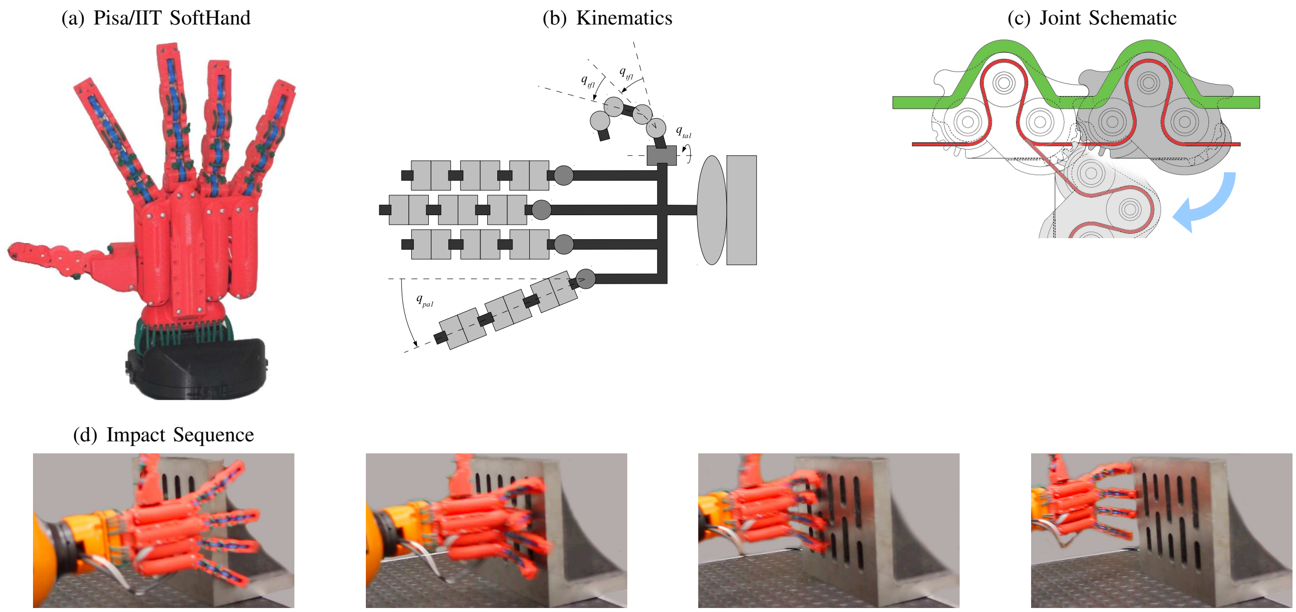

Fig. 1: 1(a) shows the Pisa/IIT SoftHand. A schematic of the hand, showing the revolute joints in dark grey and the rolling contact joints in light grey (1(b)) and a side-view schematic of the rolling contact joint in 1(c). The sequence in 1(d) shows the hand before, during, and after impact with a stiff surface.

and withstanding harsher environments.

II. MATERIALS AND METHODS

A. Overall study design

Four healthy, right-handed males participated in this study (mean age: 29.75 ± 2.01 years). Testing took place at the Istituto Italiano di Tecnologia and each testing session lasted roughly 45 minutes. Subjects lightly squeezed a ball to mimic grasping during which EMG signals from the finger flexors and extensors were used to control the grasping action of the SoftHand (Fig. 1(a)). Subjects repeated a series of grasps four times: with and without impedance control and with and without vibrotactile force feedback. Our primary outcome measure was the number of successful grasps with each testing mode. Following completion of testing, subjects were asked to answer a short questionnaire to rate the ease of use of the device and control interface.

B. The Pisa/IIT SoftHand

The Pisa/IIT SoftHand [9] (Fig. 1) was developed in a partnership between the Centro E. Piaggio of the University of Pisa and the Advanced Robotics department of the Istituto Italiano di Tecnologia in Genoa, Italy. The goal was to build a robust and safe hand at low cost, while simplifying some of the immense complexity of the hand through the use of synergies. Two design strategies were combined to achieve this result: soft synergies and underactuation. As previously mentioned, synergies are a motor control strategy that coordinates the articulation of the many joints of the hand into coherent movement patterns. By incorporating synergies into the hardware design, there is a risk of poorly approximating the object to be grasped and providing uneven force at the contact points. In soft synergies, introduced in [10], the synergy serves as a reference position for a virtual hand, thus enabling better control of the interaction forces between the hand and the grasped object through variation of the virtual hand position or the stiffness matrix connecting the virtual and real hands. A fully actuated robotic hand introduces one actuator per degree of freedom (DOF), thus increasing weight, cost, and control complexity of the final device. Underactuation [13], however, reduces the number of actuators without reducing the number of DOFs and also imparting a quality of shape adaptability on the device. These two strategies were combined to produce an "adaptive synergy" design strategy incorporating the neuroscientific basis of soft synergies with the shape adaptability of underactuation.

Using the adaptive synergy approach, a humanoid hand was designed anthropomorphically with 19 DOFs, 4 on each of 4 fingers, and 3 on the thumb (Fig. 1(b)). At rest, the hand measures roughly 23 cm from tip of the thumb to the tip of the little finger, 23.5 cm from the wrist interface to the tip of the middle finger, and 4 cm thick at the palm. The fingers are capable of flexion/extension as well as ab/adduction. For ab/adduction of the fingers and at the equivalent of the carpometacarpal joint of the thumb (responsible for rotating the thumb from lateral pinch to C grasp, for example), traditional revolute joints were employed. One of the most important considerations in the design was safety: the hand must be robust enough to be of use to humans but also compliant enough to ensure safe interaction with humans. For this reason, a soft robotics approach was taken for the rest of the joints by incorporating rolling contact joints with elastic ligaments, as seen in figure 1(c). The rolling contact joints ensure anatomically correct motion when actuated but easily disengage on impact to allow safe interaction with humans while preserving the hand. The elastic ligaments also allow deformation while ensuring the hand returns to its original configuration (Fig. 1(d)). A single tendon runs though all joints to simultaneously flex and adduct the fingers upon actuation.

The hand is actuated by a single motor to move the fingers on the path of the first synergy [14] allowing the physical hand to mold around the desired object. The motor employed is a 6 Watt Maxon motor RE-max21 with an 84:1 gear reduction and a 12 bit magnetic encoder, resolution of 0.0875^o (Austrian Microsystems AS 5045). The electronics board and battery pack are located in the back of the hand. In previous testing with a human interface [9], the hand was able to grasp a total of 107 objects spanning a wide variety of sizes, shapes, weights, and softness, including an AA battery, eyeglasses, drill, and phone. With the current motor, maximum holding torque is 2 Nm and maximum holding force is roughly 20 N perpendicular to the palm.

C. Testing

Each participant attempted to grasp 4 objects: in order, a water bottle, a screwdriver, a spray bottle, and a ball. (See Table I for dimensions and weights of the tested objects.) These objects were selected to require various typical grasp shapes and represent various levels of softness and weight. Four modes of SoftHand operation were used: in order, Standard (no impedance control or vibrotactile feedback), Impedance mode, Vibrotactile mode, and combined Vibrotactile and Impedance mode (VI mode). Because this study involved healthy subjects, the SoftHand was attached to the arm by a platform strapped to the forearm. Subjects stood in front of a table and reached to an object. Successful grasp was achieved when the SoftHand held the object securely off the surface of the table. Each grasp was attempted 3 times, for a total of 12 grasps per mode over 4 modes, for an overall total of 48 grasps. Subjects were allowed a brief familiarization period with the device in each mode to minimize learning effects; mode and grasp order were fixed for all subjects as stated above.

D. sEMG

Double differential surface electromyography (EMG) electrodes were placed on the flexor digitorum superficialis (FDS) and the extensor digitorum communis (EDC) according to the methods outlined in [15] and were used in conjunction with the Delsys-Bangoli 16 system (Delsys Inc.). A reference electrode was placed at the elbow. EMG signals were read into MATLAB Simulink (Mathworks, Inc.) using the Real-Time Windows Target feature of MATLAB. The incoming signal was filtered and rectified before being fed into the control scheme to determine user intent and required motor output and stiffness levels.

Object	Water Bottle	Screwdriver	Spray Bottle	Ball
Dims (mm)	$307 \times 55 \times 55$	$294 \times 25 \times 25$	$275 \times 84 \times 47$	$94 \times 94 \times 94$
Weight (g)	250	50	500	500

TABLE I: Dimensions and weights of test objects

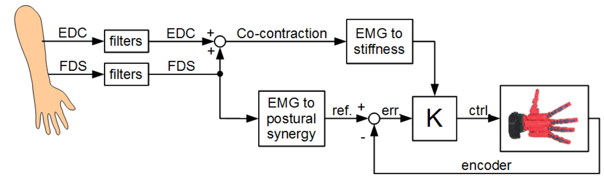

Fig. 2: Block diagram of the control pattern used to drive the Pisa/IIT SoftHand with myoelectric signals.

E. Control Architecture

The control algorithm (Fig. 2) was run in Simulink and communication with the hand as well as onboard sensing was achieved using QB Control (QB Robotics SRL), which provides embedded integrated control of dc motors and measurement of the rotary magnetic encoders and analog sensors. Prior to testing, subjects were asked to keep muscles at rest followed by repeated brief, forceful contractions. From these measures, we established minimum thresholds of activity and maximum contraction levels for scaling of the position reference and impedance signals. (Note: the goal was not to identify maximum voluntary contraction level but instead to set a comfortable maximum to allow control signal scaling for driving the SoftHand.) After filtering the EMG signals as described above, the amplitude was used to determine the position reference output to the motor. The gain used was set by the EMG amplitude maxima determined in the calibration process. Additionally, in impedance and VI modes, an index defined as a function of the sum of the FDS and EDC amplitudes was used to set the stiffness level. Therefore

$$\tau = K(FDS, EDC)[\theta_{ref}(FDS, EDC) - \theta_{msrd}], \qquad (1)$$

with τ, θ_{ref} and θ_{msrd} denoting the torque synergy, EMG driven postural equilibrium reference and measured motor angular position, respectively. The stiffness gain, K, was set to a constant value in standard and vibrotactile modes. In impedance and VI modes, K varied with time as a function of the cocontractions. In these modes, as cocontraction increased, so did the stiffness of the device to mimic innate stiffness control. The block diagram of the control architecture is provided in figure 2.

Finally, when vibrotactile feedback was used, position error was multiplied by an experimentally-determined gain to control the voltage on a small (7×24 mm) vibration motor (Precision Microdrives Ltd.), placed on the back of the hand. Higher position error correlated to higher force, which was in turn proportional to the amplitude and frequency of vibrations, thus providing force-feedback information to the user. In the case of VI mode, the feedback was scaled to changes in the stiffness to provide standardized feedback throughout the testing.

F. Questionnaire

Questionnaires were employed throughout the testing process to better evaluate the user-SoftHand control interface.

(a) reach (b) grasp (c) lift (d) release (e) withdraw

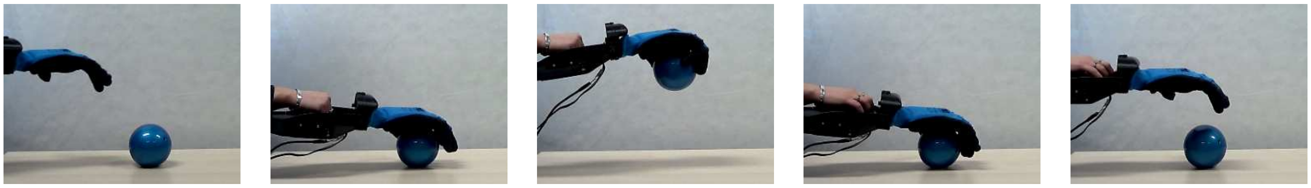

Fig. 3: Photographic sequence of a typical grasp. Five phases are noticeable: in order, reach, grasp, lift, release, and withdraw.

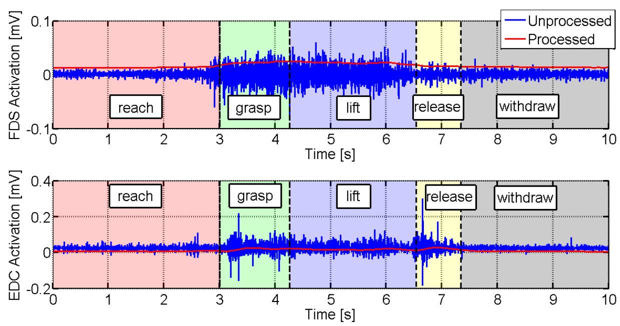

Fig. 4: Activation of FDS (top) and EDC (bottom) during a typical grasping sequence. Different colors indicate the five phases of the grasp extracted from video recordings.

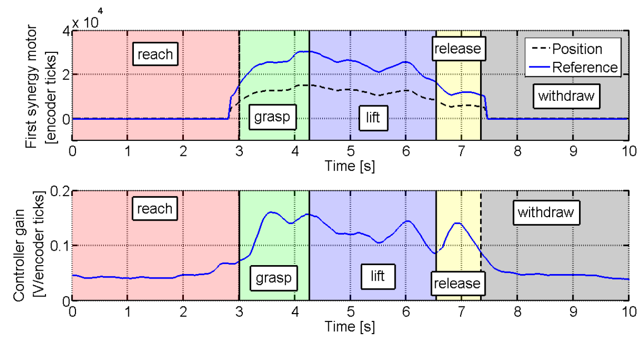

Fig. 5: Actual and reference position sent to the motor (top) and the stiffness level used (bottom), determined by cocontraction. Different colors indicate the five phases of the grasp extracted from video recordings.

Following operation of each mode, users were asked to rate the amount of physical and mental effort required to control the hand on a 5-point Likert scale. After concluding the grasping experiment, subjects were again asked to rate the overall amount of physical and mental effort as well as asked to agree or disagree with the following statements, again on a 5-point Likert scale: 1. The hand was easier to use in mode 2 (impedance). 2. The hand was easier to use with feedback. 3. The hand was easier to use with both features (VI mode).

G. Data Analysis

The number of successful grasps in each mode was tabulated and averaged across subjects. Survey data was also tabulated and is presented raw; as ordinal data, a mean cannot be calculated and the median does not accurately represent data with small n. To analyze FDS EMG data, the filtered signal used to control the SoftHand was further processed in MATLAB. A minimum threshold was established experimentally for active EMG. The EMG amplitude above this threshold was averaged and the total time spent above threshold calculated. Because muscular effort in this study is essentially isometric, mechanical work of the muscle cannot be calculated. Instead, we calculated the energy cost of the physical effort used to control the hand as the integral of the EMG amplitude over time, only considering above-threshold samples.

III. RESULTS

All subjects were able to generate sufficient EMG signal to drive the SoftHand and study procedures were well tolerated. Subjects performed the series of grasps after a brief familiarization period with the device. No difference in grasp ability was found between the four modes; out of 16 attempted grasps, subjects averaged 14.75, 15.25, 15.25, and 15 successful grasps in standard, impedance, vibrotactile, and VI modes, respectively. An example of a grasp sequence can be found in figure 3. The corresponding raw and processed EMG data as well as the position and impedance signals sent to the motor can be found in figures 4 and 5, respectively.

The results of the questionnaire on perceived physical and mental effort required to use the device revealed differences between the control modes. Figure 6 shows the results on the physical (a) and mental (b) effort questionnaire. Estimates of required mental effort in each mode roughly mirror perceived physical effort. Both impedance and vibrotactile modes required less physical and mental effort than standard mode and the VI mode showed the lowest mental effort of the four modes and lower physical effort than standard or impedance modes. This comparison between modes is reflected in the final questionnaire: when asked if the impedance mode was easier to use, 2 subjects were neutral and 2 agreed. Regarding whether control was easier with feedback, one participant disagreed, one agreed, and two strongly agreed. Finally, 3 participants agreed and one strongly agreed when asked if control was easier with both features (impedance control and vibratory feedback).

Figure 7 presents a summary of the FDS EMG data. The total time spent above threshold is presented in Fig. 7(a): subjects spent the longest time in standard mode, less time

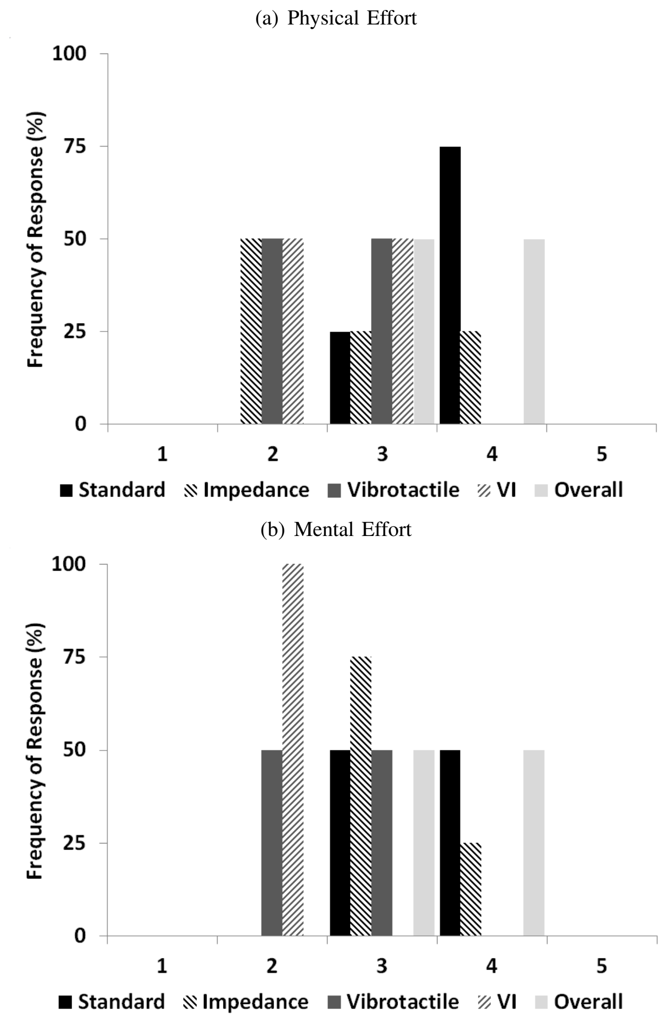

Fig. 6: Questionnaire results for physical (top) and mental (bottom) effort. Darker bars indicate lower perceived amount of effort.

in impedance and vibrotactile modes, and the least time in VI mode (mean time above threshold in s: 138.8 $\pm$ 57.9, 106.7 $\pm$ 37.4, 102.0 $\pm$ 27.9, and 80.4 $\pm$ 45.1, for standard, impedance, vibrotactile, and VI modes, respectively). We calculated both the average EMG amplitude above threshold as well as a cumulative EMG measure (Fig. 7(b), line and bars on graph, respectively). There was little difference between the modes in average EMG; the impedance mode showed slightly lower EMG levels than the other three modes (average EMG amplitude in mV, 0.0391 $\pm$ 0.0111, 0.0345 $\pm$ 0.056, 0.0393 $\pm$ 0.012, and 0.0420 $\pm$ 0.038, for standard, impedance, vibrotactile, and VI modes, respectively). As an estimate of total effort, cumulative EMG amplitude was also calculated. Similar to the time spent above threshold in each mode, the highest energy cost was seen in the standard mode, while lowest was in VI mode.

IV. CONCLUSIONS

Overall, the results of this study suggest the SoftHand could be used successfully as a myoelectric prosthesis. With a short familiarization period (less than five minutes), subjects were able to successfully grasp and release roughly 15 out of 16 trials in all modes. Subjects reported lower physical and mental effort while using impedance and vibrotactile feedback modes compared to standard mode and least effort in the combined VI mode. Anecdotally, one subject advocated for the combined VI mode stating that control took less concentration with feedback and less physical effort with impedance control.

These qualitative results agree with the quantitative EMG data: subjects activated the flexors for less time in impedance and vibrotactile modes compared to standard mode and the least time in VI mode. A learning effect is possibly a confounding factor in this analysis; however, a familiarization period was included for each mode to remove the steepest part of the learning curve, and the high grasp ability across all modes suggests there was minimal learning to be gained from the task. Interestingly, the time for both single-feature control modes (impedance and vibrotactile) was similar and higher than the combined mode, suggesting increased benefit from using both strategies together. Subjects had slightly higher

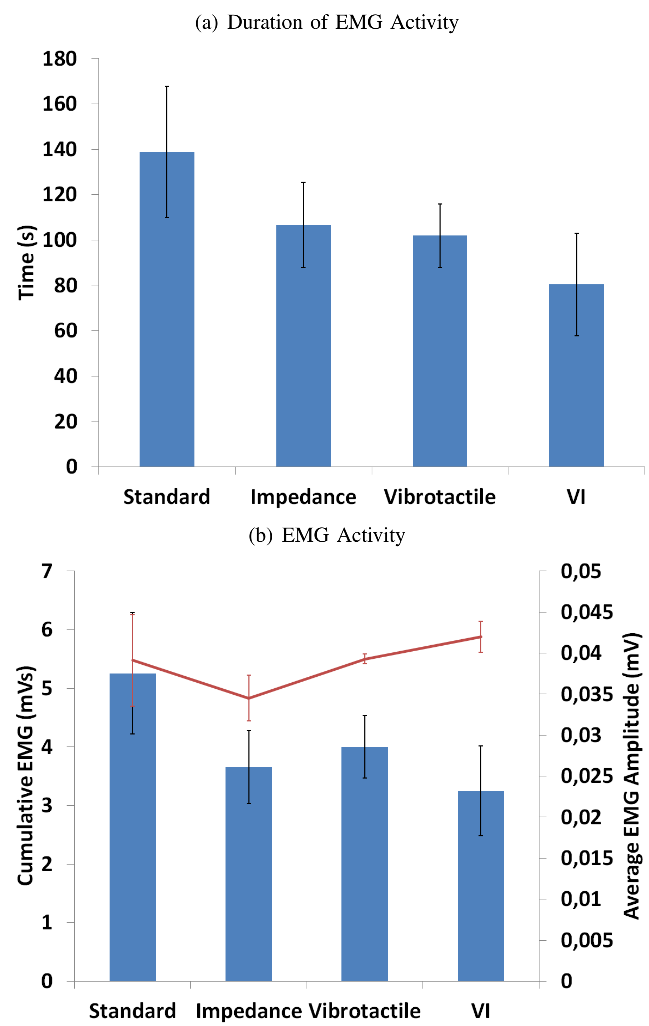

Fig. 7: Time spent above threshold averaged across subjects (top). Average FDS EMG amplitude (bottom, bars) and cumulative EMG (bottom, line).

energy cost in vibrotactile mode compared to impedance and VI modes. The vibrotactile motor used in this study had low resolution, thus it is possible subjects exaggerated their contractions to benefit from the feedback. The results suggest added benefit from the impedance controller and vibrotactile feedback; however, since functionality was still high with the standard controller, this may be a feasible alternative in users with limited myoelectric control or diminished cognitive function. This study shows the feasibility of transferring complexity from the user and control architecture of a myoelectric prosthesis to the hardware to decrease cost and physical and cognitive load without sacrificing performance. Future work will include testing with amputees as well as improving the sensitivity of the current control system.

V. ACKNOWLEDGMENTS

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